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4/21/2024
CS 474

Semantic Segmentation for Hurricane Disaster Recovery

Overview:
The aim of this work is to produce a high quality semantic segmentation computer vision model capable of classifying aerial imagery after hurricanes to assist with property damage claims based on flood loss.

Motivation:
After severe hurricanes, property insurers become overwhelmed with property damage claims, specifically for flood loss. Being able to remotely evaluate the validity of these claims at a large scale can greatly increase the turnover time required to distribute insurance proceeds to clients.

Data:
The aerial images used for training come from imagery after Hurricane Harvey. There are 261 images with their associated masks. There are a total of 25 classes in the masks. The classes are as follows. (0: Background, 1: Property Roof, 2: Secondary Structure, 3: Swimming Pool, 4: Vehicle, 5: Grass, 6: Trees / Shrub, 7: Solar Panels, 8: Chimney, 9: Street Light, 10: Window, 11: Satellite Antenna, 12: Garbage Bins, 13: Trampoline, 14: Road/Highway, 15: Under Construction / In Progress Status, 16: Power Lines & Cables, 17: Water Tank / Oil Tank, 18: Parking Area - Commercial, 19: Sports Complex / Arena, 20: Industrial Site, 21: Dense Vegetation / Forest, 22: Water Body, 23: Flooded, and 24: Boat).

The dataset can be found at this line:
https://figshare.com/collections/semantic_segmentation_satellite_imagery/6026765

The majority of the classes are background, grass, trees/ shrubs, and flooded. There are some very small minority classes such as solar panels, chimneys, boats, etc.

An example image and associated mask can be found in (Figure 1) while the breakdown of the class percentages can be found lower in (Table 1).

Unfortunately there's one thing to note here - **the masks are not 100% accurate and frequently miss labels**. So, when the model accurately identifies a pixel, occasionally it is told that it predicted incorrectly when in reality the model did predict it correctly.

Figure 1

Example mask and image found in the training dataset

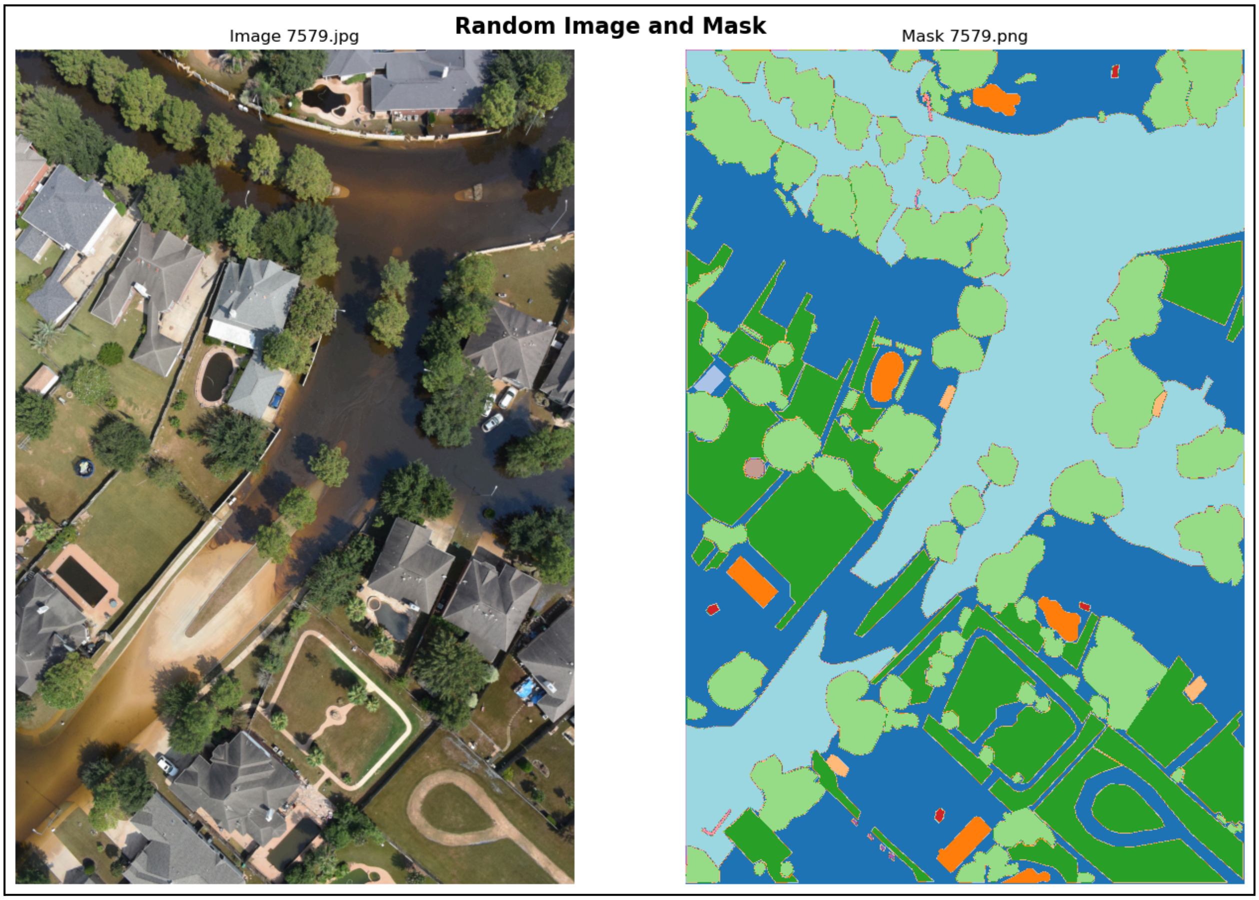

Table 1

Breakdown of the classes found in (Figure 1)

Class	Name	Percentage(%)	Class	Name	Percentage(%)
0	Background	16.48%	6	Trees / Shrubs	22.38%
1	Property Roof	14.87%	8	Chimney	0.07%
2	Secondary Structure	0.10%	9	Street Light	0.06%
3	Swimming Pool	1.32%	10	Window	0.02%
4	Vehicle	0.21%	13	Trampoline	0.07%
5	Grass	18.30%	23	Flooded	26.12%

<u>Results & Methods:</u>

To create an accurate metric the images were split into a training and validation set. The metric used to evaluate performance was a custom Intersection over Union metric. A Unet model with a pre-trained backbone from the ImageNet1k dataset was fine tuned to our dataset. Data augmentation was also used, specifically random rotation between 0-360 degrees and a brightness change. Our training IoU was able to improve from 0 to 0.20. The model can accurately identify the majority classes but struggles with the minority classes. Some extra work that could improve the model is to add heavier weights to the minority classes and or add a region term to the loss function and penalize labeling adjacent pixels differently to try and obtain smooth labels.The results from our model on a sample validation image can be found in (Figure 2).

Figure 2

Model prediction on sample validation image